E-learning intention of students with general anxiety: evidence from the first wave of COVID-19 pandemic in China

Abstract

Background: The COVID-19 pandemic has exposed the need to address the mental health issues for the future adoption of e-learning among massive students in higher education. This study takes a lead to investigate whether and how general anxiety will influence college students' e-learning intention to provide knowledge to better improve the e-learning technology.

Methods: We adopted the Technology acceptance model (TAM) to examine the difference between students with and without general anxiety in the e-learning intention where the students are classified based on the General Anxiety Disorder-2 scale. The model is empirically analyzed based on a survey of 512 college students in China regarding their e-learning experience in the first wave of the COVID-19 pandemic.

Results: Results demonstrate that the TAM is powerful in explaining the e-learning intention among college students with general anxiety. Besides, all effects associated with perceived usefulness (PU) are reinforced while those associated with perceived ease of use (PEOU) are attenuated in the anxiety group. The results suggest that instructors and higher education institutions should take advantage of the significant PU-intention relationship by providing quality e-learning, which is paramount to coping with the general anxiety among students.

Limitations: This study provides a prototype attempt to investigate the influence of anxiety on e-learning where the different types of anxiety sources are synthesized. However, anxiety can stem from internal sources (computer anxiety, academic stress) and external sources (fear of the virus, lack of social interaction), which requires further investigations.

Keywords: E-learning, anxiety, TAM, COVID-19, GAD

1 Introduction

Information and communication technology (ICT) has significantly nudged the development of e-learning in higher education. With the compelling advantage in venues accessibility zzz(Bao, 2020; Szopiński & Bachnik, 2022) and student-centered education (Dhawan, 2020), e-learning is considered a future education paradigm to an alternative face-to-face offerings and a burgeoning standard of higher education for the future generation Z (Hsu, *et al.*, 2018). However, the current form of e-learning is not perfect and numerous scholars have questioned the readiness (Rapanta, *et al.*, 2020; Scherer, *et al.*, 2021) and fitness (Bao, 2020; Szopiński & Bachnik, 2022) for the future massive adoption of e-learning in higher education. Thus, it is important to revisit all possible scenarios to provide nuanced insights into e-learning adoption, which in turn facilitate enhanced technology development.

The massive overnight "migration" from traditional in-class face-to-face education to online education during the COVID-19 emergency has provided a test field to examine the capability of e-learning in massive adoption. The sudden outbreak of COVID-19 has unprecedentedly forced universities worldwide campus lockdown and to launch online programs to keep the education functional (Bao, 2020). The makeshift of education to e-learning has caused tremendous difficulties for higher education alike and it has sparked extensive discussions in the research community. While extensive COVID-19 related e-learning literature is majorly revolving around the capability of e-learning in realizing the education functions: ICT capability or adaptability (Mailizar, et al., 2021; Tarhini, et al., 2014), the skill sets of the instructors (Szopiński & Bachnik, 2022), the same necessity is needed to tackle mental health conditions among students in e-learning adoption.

The mental health vulnerability of college students in the compounded e-learning and stress environment was exposed during the sudden outbreak of the COVID-19. According to the study by Li, *et al.* (2021), the prevalence of depression and anxiety for college students worldwide were 39% and 36%, respectively during the COVID-19 pandemic. Further, cognitive load theory posits that an extra account of mental efforts is required to cope with anxiety, resulting in less mental effort available for e-learning. Therefore, it is reasonable to assume that the influence of anxiety on e-learning adoption cannot be overlooked. To address this concern, existing debates are largely focused on the anxiety associated with e-learning itself, computer anxiety (Abdullah & Ward, 2016; Šumak, *et al.*, 2011), however, anxiety can stem from multiple sources such as fear of the virus (Hoque, *et al.*, 2021; Li, *et al.*, 2021), lack of social interaction (Szopiński & Bachnik, 2022), and academic stress (Chen, *et al.*, 2020) as well. Given that certain levels of anxiety or other mental health issues are prone to sustain beyond the COVID-19 pandemic, a need, therefore, emerges to investigate whether e-learning can withstand conditions and changes imposed by anxiety. As such, this study is conducted to address two overarching research questions: (1) Will the anxiety level have a moderating effect on students' adoption of e-learning during the Covid-19; (2)if yes, how does the anxiety level moderate the relationship of the TAM constructs in terms of significant level and effect size?

To address the two research questions, this study aims to investigate the differences in e-learning intention among students with and without general anxiety in higher education to provide nuanced insights into the potential influence of anxiety and future changes for e-learning. Specifically, we adopted the TAM model to examine the difference between students with and without anxiety in the e-learning intention where the students are classified based on the GAD-2 scale. 512 respondents from college students during the first wave of the COVID-19 pandemic were collected to provide empirical evidence. Findings reveal that all perceptions in the TAM constructs are reduced in the anxiety group, however, the TAM remains applicable for the anxiety group. Besides, compared to the non-anxiety group, all effects associated with PU are reinforced while those associated with PEOU are attenuated in the anxiety group. This study contributes to a better understanding of the influence of anxiety on e-learning intention, which further provides nuanced knowledge on the future adoption of e-learning for massive students in higher education. We advocate instructors and higher education institutions should take advantage of the significant PU-intention relationship by providing quality e-learning, which is paramount to coping with the anxiety among students. Apart from that, the technology developers need to appropriately improve the human-computer interface (PEOU) to enhance students' perception of performance benefit (PU) from the e-learning, which will, in turn, motivate their e-learning intention.

The remainder of this paper is structured as follows. The theoretical background is presented in section two. Section three and fourth describe the methodology and result respectively. This is followed by analyzing the research results and discussing the practical and theoretical implications in section five. The conclusion, limitation, and scope for future research are summarized in the final section.

2 Literature review

2.1 E-learning and the e-learning intention

The term e-learning can manifest multiple derivatives such as web-based learning, blended learning, distant learning, etc. In all, e-learning can be widely defined as the use of ICT as a medium to facilitate the learning process (Al-Fraihat, *et al.*, 2020; Sun, *et al.*, 2008) or enhance the interaction between students and instructors (Singh & Thurman, 2019). Existing debates on e-learning are majorly revolving around three aspects. First, with the compelling accessibility, e-learning has been deemed a solution for an enhanced education opportunity (Benson, 2002). Under such environments, students can learn and interact with instructors without physically being in the same place (Singh & Thurman, 2019). Another interesting aspect that is widely discussed is student-centered flexibility (Dhawan, 2020). Students can customize their study plans and time based on their schedules. Hsu, *et al.* (2012) argued that such a student-centered paradigm would be the burgeoning standard in education. Last but not least, numerous scholars have concerned the psychological impact of e-learning on students. While many argued e-learning can create a virtual environment that can serve as an alternative community for social interaction (Dhawan, 2020), others highlighted the importance to address computer anxiety (Abdullah & Ward, 2016; Baby & Kannammal, 2020) and environmental isolation issues associated with e-learning (Fawaz & Samaha, 2021). In all, similar to many other online social communities, the influence of e-learning on students is mixed (Ivie, *et al.*, 2020; Liu, *et al.*, 2020).

Other scholars (Abdullah & Ward, 2016; Šumak, *et al.*, 2011) evaluated the effectiveness of e-learning through students' attitudes. The technology acceptance model (TAM) is a common ground theory for studying what influential factors determine users' behavior intentions (Šumak, et al., 2011). The TAM, deriving from the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), was proposed by Davis (1989) to explain the behavioral intention of users regarding the acceptance of the information system. In the context of e-learning, TAM presumes that students' acceptance of e-learning is determined by their behavior intention, which, in turn, is directly explained by two constructs, namely perceived usefulness and perceived ease of use, where the former, refers to “a user believes in the existence of a positive use-performance” while the latter refers to a user believes in the effortlessness of the system use (Davis, 1985, 1989). In such a sense, the effectiveness of e-learning can be assessed based on students’ perception of its usefulness and ease of use in e-learning. Further, these two constructs can be influenced by other external stimuli (Davis, 1985) such as self-efficacy, subjective norm, enjoyment, and technology anxiety (Abdullah & Ward, 2016). While the TAM is extensively used to understand students’ acceptance on e-learning, these studies are largely focused on the internal features and capabilities that motivate students’ e-learning intention. E-learning during the COVID-19 pandemic, however, is compounded with complex stress external environments, which only received limited research attention (Mailizar, *et al.*, 2021). Therefore, a need emerges to revisit the external feature of e-learning during the COVID-19 pandemic.

2.2 E-learning during the COVID-19 pandemic

The demand for e-learning has been significantly boosted during the COVID-19 pandemic. The outbreak of the pandemic has forced campus lockdown temporarily and universities worldwide cannot but rely on e-learning to education functional or at least available (Bao, 2020). The COVID-19 pandemic has shown the lucrative side of e-learning. The emergence of e-learning has largely facilitated the accessibility of education and the synchronous learning environment is prone to reduce the distance barrier by enabling online interactions. For instance, during the COVID-19 pandemic, Peking University launched 4,437 online courses to make education available for over 44,700 students (Bao, 2020). Students can receive education from homes or dorms without physically gathering. Dhawan (2020) argued that e-learning is a panacea in the time of the COVID-19 crisis.

While the accessibility and flexibility of e-learning during the COVID-19 pandemic are extensively acknowledged (Dhawan, 2020; Szopiński & Bachnik, 2022), the COVID-19 pandemic exposed the shortcomings of e-learning regarding how it provides quality education. Quality e-learning requires consistent planning and development, which is not available for such an abrupt mass migration to e-learning during the COVID-19 pandemic (Carey, 2020). In addition, it takes care and time for both students and teachers to be prepared and trained to engage in online interaction (Cong, 2020). The sudden adoption of e-learning during the Covid-19 has put both the teachers and students under unprecedented pressure, which may inhibit their attitude toward e-learning. Besides, Pokhrel and Chhetri (2021) posited that e-learning is prone to intensify the divide in students’ e-learning motivation: the innately motivated students are likely to take advantage of e-learning, which is relatively unaffected by the shift to e-learning while those students weak in learning are confronted with significant difficulties in e-learning adaption.

In addition to the technical issues, mental health issues caused by the sudden adoption of e-learning (Fawaz & Samaha, 2021), coupled with the absence of face-to-face interactions (Song, *et al.*, 2004), are prone to expose the psychological vulnerability of the students, which in turn may degrade the effectiveness and quality of e-learning. First, the sudden adoption of e-learning could impose extra computer anxiety on students which may further evolve into depression symptoms. For instance, Fawaz and Samaha (2021) posited that the sudden shift to e-learning has caused stressful loads which started to give rise to anxiety and depressive symptomatology among university students. Further, as social distancing is preeminent at this stage, universities students are confronting challenges not only from the sudden adoption of e-learning but also stresses and emotions caused by the pandemic outbreak (Nikou & Maslov, 2021). According to a meta-analysis of 27 studies of 706,415 students by Li, *et al.* (2021), the prevalence of depression and anxiety during the COVID-19 pandemic was 39% and 36% respectively. Given that anxiety is a prevailing symptom for universities students during the COVID-19 pandemic, it is necessary to investigate its influence on e-learning intention.

2.3 The influence of GAD on e-learning intention

The need for addressing mental health issues has been repeatedly highlighted in the literature (Dhawan, 2020; Grey, *et al.*, 2020; Shensa, *et al.*, 2020; Szopiński & Bachnik, 2022; Yao, *et al.*, 2021). Prior studies have largely focused on the impact of computer anxiety on e-learning intention and computer anxiety has been introduced as a common external variable of the TAM model(Abdullah & Ward, 2016; Šumak, *et al.*, 2011; Venkatesh, *et al.*, 2003). According to Venkatesh, *et al.* (2003), computer anxiety is referred to an individual’s tendency to feel insecure, apprehensive, or fearful about the use of computers. There is extensive theoretical and empirical evidence showing that computer anxiety is associated with avoidance or lesser use of e-learning (Abdullah & Ward, 2016; Al-alak & Alnawas, 2011; Šumak, *et al.*, 2011). Specifically, computer anxiety is found to negatively and significantly affect students’ intention toward e-learning (Al-alak & Alnawas, 2011). Further, in a meta-analysis by Abdullah and Ward (2016), the results showed that computer anxiety is negative relative to the perceived ease of use of the e-learning and the effect size (-0.199) is small to medium. Besides, the results also implied that the relationship between computer anxiety and perceived usefulness is positive (0.070).

Compared to the prior e-learning studies that have largely focused on computer anxiety, COVID-19 pandemic-related e-learning literature has highlighted the pivot role to cope with emotions and stresses induced by the external environment. However, while there is a consensus that the relationship between computer anxiety and perceived ease of use is negative, the relationship between external environment anxiety and e-learning intention is mixed. On the one hand, the rapidly increasing number of confirmed cases and deaths due to the COVID-19 pandemic has triggered stress among students, which in turn may impose negative influences on the students' e-learning intention and psychological well-being (Oducado & Estoque, 2021). On the other hand, e-learning can form an online social community alternative to face-to-face social interactions (e.g. voicing fear, expressing feelings, exchanging social supports) (Yan, 2020), which can, can further shape the mental resilience of the students towards traumatic events (Marzouki, *et al.*, 2021). Therefore, the external emotions and stresses are prone to motivate students' active engagement in e-learning (Doyumgaç, *et al.*, 2021; Mukhtar, *et al.*, 2020). In all, the role of external emotions and stresses on e-learning has sparked discussion in the research communities, however, the findings remain piecemeal and inconclusive. Specifically, limited empirical evidence provides nuanced insights into how external anxiety impacts e-learning intention. To address this, this study takes the lead to investigate the impact of anxiety on e-learning by comparing the difference between anxiety and non-anxiety groups on TAM constructs.

3 Methodology

3.1 Participants and procedure

This study was designed to examine (1) whether the anxiety will influence students' continuance intention in e-learning in higher education (2) if yes, what are the exact effects. The background was set as the massive adoption of e-learning for universities students in China, which was during the first wave of the COVID-19 outbreak (spring semester of 2020). Empirical data were collected through an online survey. We developed an online questionnaire and share the link of the survey sent through WeChat to university students that have undergone e-learning during the spring semester of 2020. To ensure the representative of the participants, we distributed the questionnaire to university students in six major cities including, Beijing, Qingdao, Xiamen, Shanghai, Wuhan, and Chongqing, which covers the north, south, center, and west part of China. Besides, to cover participants in non-above mentioned areas, the questionnaire was also distributed online through Weibo. In the questionnaire, the first section encompasses a brief description of the purpose of this study and a statement clarifying that all the information in the survey is confidential and for research purposes only. The second section starts with a question asking whether or not she or he has undergone e-learning during the spring semester of 2020 and agreed to participate in this survey. Once confirmed, participants are required to fill out the set of questionnaires online within a certain limit of time. In all, a total of 613 respondents were recruited and the survey yielded a total of 512 complete, valid responses (response rate 84%) for the data analysis.

3.2 Construct measurement

The set of questionnaires involved in this study was mainly composed of three sections. The first section is the sociodemographic characteristic which was self-designed and included questions regarding sex, age, place of residence, and school year. The general anxiety level was measured using the general anxiety disorder with 2 core items (GAD2)(Kroenke, *et al.*, 2007). The students are asked how often they have been bothered by the following two problems during the e-learning in the first wave of COVID-19: (1) feeling nervous, anxious, or on edge; (2) not being able to stop or control worrying during. The two questions are measured based on a 4-point scale, not at all (score 0), several days (score 1), more than half the days (score 2), and nearly every day (score 3). According to Kroenke, *et al.* (2007) using a cut-off of 3 the GAD-2 has a sensitivity of 86% and specificity of 83% for the diagnosis of generalized anxiety disorder, thus, we adopt the threshold of 3 as the separation of non-anxiety students and anxiety students. In the third section, all the measurement items for the TAM constructs were adopted from prior studies (Chang, 2010; Kim, *et al.*, 2010; Wu & Chen, 2017; Wu & Zhang, 2014) and adapted to suit the context of this study. All of the measurement items used a five-point Likert scale, anchored from strongly agree (1) to strongly disagree (5). Moreover, since the survey is in Chinese, this study followed the back-translation method (Bhalla & Lin, 1987). The wording, legibility, and suitability of the questionnaire were also checked by 4 graduate students and 2 undergraduate students before online delivery. The detailed constructs and measurements are listed in Appendix 1.

3.3 Statistics analysis

To address the two research questions, the analysis encompasses two sections, respectively. The first section is an analysis of variance (ANOVA), aiming to identify whether the control group (non-anxiety) and the anxiety group have a significantly different perceptions of the TAM constructs. The ANOVA was performed using SPSS 26.0. The second section is designed to validate whether the TAM model is applicable for the anxiety group and if yes, compare the inter-group size effect differences. We followed the two-step Structural Equational Model (SEM) approach recommended by Anderson and Gerbing (1988) for the data analysis. With comprehensive techniques of SEM, the AMOS 26 was adopted for the analysis.

4 Results

4.1 ANOVA analysis

Table 1 ANOVA analysis result of TAM constructs

		Non-anxiety Group (N=144)		Anxiety Group (N=368)		
		Mean	SD	Mean	SD	P value
PU	PU1	2.278	1.041	2.755	0.937	0.000***
	PU2	2.410	1.131	2.867	1.013	0.000***
	PU3	2.375	1.057	2.810	0.969	0.000***
PEOU	PEOU1	2.021	0.971	2.370	0.892	0.000***
	PEOU2	1.854	0.931	2.122	0.815	0.001***
	PEOU3	1.764	0.924	2.114	0.860	0.000***
ATT	ATT1	2.132	1.039	2.462	0.900	0.000***
	ATT2	2.056	1.082	2.457	0.915	0.000***
	ATT3	2.000	0.877	2.315	0.869	0.000***
CI	CI1	2.014	1.051	2.413	0.975	0.000***
	CI2	2.021	1.137	2.432	1.034	0.000***
	CI3	2.097	1.185	2.486	1.047	0.000***

To examine whether the GAD will influence students' e-learning continuance intention, the respondents were further classified into two groups, the anxiety group, and the non-anxiety group. According to Kroenke, *et al.* (2007), a total GAD2 score of 3 or more can be considered a certain level of general anxiety. Thus, students with a total self-report GAD2 score were attributed to the anxiety group while the rest were attributed to the non-anxiety group.

In all, among 512 respondents, 368 (72%) students are reported to have a certain level of general anxiety. This result confirms with existing studies that GAD is a major concern during the COVID-19 (Hoque, *et al.*, 2021; Lebel, *et al.*, 2020). The ANOVA analysis result is listed in Table 1. For all the measurement items, the mean score in the non-anxiety group is smaller than the mean score in the anxiety group. Given that the five-point Likert scale we used is anchored from strongly agree (1) to strongly disagree (5), it suggests that the level of PU, PEOU, ATT, and CI in the non-anxiety group are all higher than that in the anxiety group. Further, the inter-group difference is largest in PU (0.456) are smallest in PEOU (0.322), suggesting that the anxiety may have the most influence on the PU and the least influence on PEOU. Despite the inter-group difference, all the measurement items score an average of less than 3(neutral), implying that anxiety may influence the level of students' e-learning intention, but not necessarily alter their attitude.

4.2 Structural Equation Model

4.2.1 Measurement model

The confirmatory factor analysis (CFA) was applied to assess the validity of the TAM constructs. The reliability was assessed by indexes of the factor loading, Cronbach's α, and composite reliability (CR).

The factor loading measures the indicator reliability of the model. According to Hair (2009), outer loading for the indicators above 0.7 is considered good reliability while between 0.35 and 0.7 is considered acceptable. The internal consistency reliability was measured using Cronbach's α, composite reliability (CR). Referring to Urbach and Ahlemann (2010), the recommended value for both should be above 0.7. The reliability analysis results of this study are listed in Table 2. All factor loading exceeds 0.7, suggesting good internal reality. All composite reliability values Cronbach's α values are larger than 0.7, indicating good internal consistency reliability.

The validity of the measurement model is assessed based on the convergent validity and discriminant validity. The convergent validity is measured based on the average variance extracted (AVE). The recommended value for AVE should be ≥0.5 (Fornell & Larcker, 1981). The discriminant validity is assessed based on the cross-loadings. As suggested by Urbach and Ahlemann (2010), the square root of the AVE from the construct should be greater than the correlation shared between the construct and other constructs in the model. The convergent validity and the discriminant validity results of the constructs are listed in Table 2 and Table 3, respectively. Based on the results, criteria for both convergent validity and discriminant validity are met, indicating good model validity.

Table 2 Reliability and convergent validity analysis

	Items	Standardized Factor Loading	Composite Reliability	AVE	Alpha
Continuance intention (CI)	CI1	0.937	0.952	0.868	0.940
	CI2	0.964			
	CI3	0.893			
Attitude (ATT)	ATT1	0.825	0.885	0.720	0.913
	ATT2	0.849			
	ATT3	0.871			
Perceived Usefulness (PU)	PU1	0.903	0.940	0.839	0.939
	PU2	0.927			
	PU3	0.917			
Perceive ease of use (PEOU)	PEOU1	0.905	0.873	0.697	0.893
	PEOU2	0.833			
	PEOU3	0.761			

Table 3 Discriminant validity analysis

	CI	ATT	PU	PEOU
CI	0.965			
ATT	0.913	0.921		
PU	0.742	0.878	0.957	
PEOU	0.555	0.752	0.653	0.913

4.3.2 Structural model

The structural model reflecting the assumed linear, causal relationships among constructs were tested. Model fit indices include the chi-square test statistic, the goodness of fit index (GFI), the non-normed fit index (NNFI), the comparative fit index (CFI), and the root mean square error of approximation

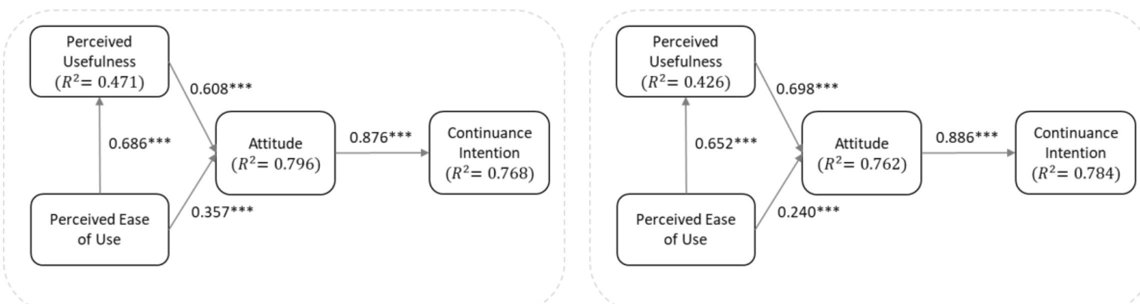
(RMSEA) are used to assess the model fit. Table 4 listed the recommended value, and the reference for all the model fit indices. By comparing the results and recommended value in Table 4, the proposed model was within accepted thresholds.

Table 4 Model fit indices for the structural model

Model fit indices	Results	Recommended value
CHI-SQAURE	3.609	⩽5
MNFI	0.975	⩾0.9
CFI	0.982	⩾0.9
RMSEA	0.071	≤0.1

4.2.3 TAM effects

TAM is widely adopted for understanding students' intentions in e-learning (Abdullah & Ward, 2016). In order to examine whether the TAM model is applicable in e-learning during the COVID-19 pandemic, empirical data for both the non-anxiety group and the anxiety group are inputted into the model and the results are depicted in Figure 1.



1a) model testing results for non-anxiety group   1b) model testing results for anxiety group

Figure 1 TAM model testing results

For the non-anxiety group, the results (Figure 1a) overlap with previous studies (Abdullah & Ward, 2016). that students' continuance intention in e-learning can be addressed using the TAM. Specifically, all the hypotheses in the TAM model are supported. The PEOU is significantly ($p < 0.001$) and positive ($\beta = 0.686$) related to the PU. Both PU ($\beta = 0.608$) and PEOU（$\beta = 0.357$）have a positive and significant ($p < 0.001$) relationship with ATT, however, the size effect between PU and ATT is much larger. The ATT is also found significantly ($p < 0.001$) and positively ($\beta = 0.876$) related to CI.

For the anxiety group, Somewhat similarly, the results (Figure 1b) confirm that the continuance intention in e-learning for the anxiety group could be explained using the TAM model as well. Similar to the results for the non-anxiety group, all the hypotheses in the TAM model for the anxiety group are supported. Specifically, the PEOU is significantly and positively ($\beta = 0.652$) related to PU. Both PEOU ($\beta = 0.240$) and PU ($\beta = 0.698$) have a significant and positive relationship with the ATT. Besides, the ATT is significantly and positively ($\beta = 0.886$) related to CI.

Table 5 Direct, indirect, and total effect on continuance intention

	Non-anxiety Group			Anxiety Group		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
PEOU->PU	0.686	-	0.686	0.652	-	0.652
PEOU->ATT	0.357	0.418	0.775	0.240	0.455	0.695
PEOU->CI	-	0.679	0.679	-	0.615	0.615
PU->ATT	0.608	-	0.608	0.698	-	0.698
PU->CI	-	0.533	0.533	-	0.618	0.618
ATT->CI	0.876	-	0.876	0.886	-	0.886

Regarding the explanatory ability, by comparison, the r-square value for PU and ATT is larger in the non-anxiety group while the r-square value for CI is larger in the anxiety group. Despite the minor difference, both models have demonstrated the good explanatory ability of TAM on students' e-learning intention.

With the aforementioned path analysis results, direct effect, indirect effect, and total effect between variables are arranged in order the understand the influence difference between the two groups. The effect analyzes are listed in Table 5. By comparison, there are two differences worth mentioning. First, both the direct and total effects between the PEOU and ATT tend to decline in the anxiety group. For instance, the effect size is 0.357 and 0.775 respectively in the non-anxiety group while it is 0.240 and 0.695 respectively in the anxiety group. Second, the total effect between PU and CI tends to increase while the total effect between PEOU and CI tends to decrease in the anxiety group. For instance, the PU-CI total effect climbs from 0.533 to 0.618 in the anxiety group; the PEOU-CI effect drops from 0.679 to 0.615 in the anxiety group. All combined, both results may imply that anxiety may reinforce the influence of PU and attenuate the influence of PEOU.

5 Discussion

In this section, we organized the discussion into four sub-sections. First, the intergroup difference between the non-anxiety and the anxiety group is analyzed to provide nuanced insights into the influence of general anxiety on e-learning intention. This is followed by a further discussion on the influence mechanism. The practical and theoretical implications are presented in sub-section three and four accordingly.

5.1 Influence of anxiety on TAM constructs

Of all the findings, the most important is the empirical results confirm the existence of anxiety from the external environment among the e-learning community during the COVID-19 pandemic and highlight that such anxiety cannot be overlooked. There are two findings worth mentioning. First, among the 512 respondents in the survey, 72% of them self-reported a certain level of general anxiety according to GAD-2. This result is consistent with previous studies calling for attention to address mental health issues for college students during the COVID-19 pandemic (Chen, *et al.*, 2020; Gonzales, *et al.*, 2020; Li, *et al.*, 2021). However, the anxiety rate is much higher in this study than in the meta-analysis result by Li, *et al.* (2021), in which the mean anxiety rate from 27 studies on college students is 36%. One possible explanation for the difference is that studies by Li, *et al.* (2021) are majorly focused on the anxiety associated directly with the pandemic, however, the anxiety of college students can stem from multiple sources such as fear of the virus (Hoque, *et al.*, 2021; Li, *et al.*, 2021), lack of social interaction (Szopiński & Bachnik, 2022), computer anxiety (Abdullah & Ward, 2016; Šumak, *et al.*, 2011), and academic stress (Chen, *et al.*, 2020). In another study, Chen, *et al.* (2020) argued that college students' anxiety during the COVID-19 pandemic is compounded with academic stress, resulting in a high anxiety rate(69%) similar to the result in this study. The high anxiety rate aligns with the setting in this study that anxiety originated from both the external (e.g., fear of the virus, lack of social interaction) and the internal (e.g., computer anxiety, academic stress). Another possible cause for the difference in the anxiety rate may be attributed to the survey time. In Li, *et al.* (2021), the analysis result showed that the anxiety rate after March 1 is significantly higher than it before March 1. Since the survey is performing in a much later time and it covers the entire period of spring semester of 2020 (Feb to June), it is reasonable to assume the anxiety rate is higher.

The second finding from the ANOVA analysis is that anxiety may have an inhibiting effect on the e-learning adaption among college students. Cognitive load theory (Sweller, 1988) explains that this is because a more amount of mental effort needed to be allocated to address the anxiety issues which in turn makes less mental effort available for actually adapting to e-learning (Porumbescu, *et al.*, 2017), thus resulting in a lower level of PU, PEOU, ATT, and CI. This result overlaps with prior studies that focused on computer anxiety (Abdullah & Ward, 2016; Al-alak & Alnawas, 2011; Šumak, et al., 2011) in that anxiety (computer anxiety) is negatively associated with the perceived ease of use, attitude, and continuance intention in e-learning. Differently, the anxiety is identified to be negatively associated with PU in this study while in prior studies (Abdullah & Ward, 2016; Venkatesh, *et al.*, 2003), the relationship between anxiety and PU is insignificant. One possible explanation, according to the TAM, is that anxiety may indirectly influence PU through PEOU, resulting in a negative association.

5.2 Influential mechanism of anxiety on e-learning intention

Results in Figure 1 and Table 5 point to an important influential mechanism of anxiety on e-learning: anxiety tends to reinforce the influence of PU on e-learning intention and attenuate the influence of PEOU on e-learning intention. In hindsight, the increase in the PU-intention relationship in the anxiety group makes sense conceptually.

Self-determination theory (Deci & Ryan, 1985) posits that intrinsic motivation is the primary type of motivation in individual intention. PU on performance enhancement, referring to as the engagement in activities for their own sake, is closely related to the intrinsic motivation, while the PEOU, refers to the perception of whether the e-learning is free of effort, which is largely attributed to external motivation. Then, according to Davis (1989). students are driven to adopt e-learning primarily because they believe that it will improve their performance, and secondarily for whether it is free of effort to use its functions. This finding is concurrent with prior e-learning studies (Islam, 2014; Mohammadi, 2015; Šumak, *et al.*, 2011) that the influence between PU and intention is much stronger and directly than that between PEOU and intention. Further, Self-determination theory (Deci & Ryan, 1985) also advocates that the external environment can facilitate intrinsic motivation by supporting people's inherent psychological needs. Mental health issues in the anxiety group can intensify students' inherent psychological needs, which in turn trigger their seeking for support in the e-learning, resulting in higher e-learning intention. For instance, students with anxiety from the external environment (fear of the disease, lack of social interaction) may more actively engage in e-learning to seek social interactions (Dhawan, 2020) and social support (Grey, *et al.*, 2020; Yao, *et al.*, 2021). Students with anxiety from academic stress may take advantage of this available learning platform to improve their academic performance regardless of the difficulties in the ease of use (Oducado & Estoque, 2021). Thus the anxiety is prone to strengthen the PU-intention effect and undermine the PEOU-intention effect.

5.3 Practical implications

The study has three major implications for practitioners. First, different from previous studies that focused on computer anxiety, this study introduced a synthesized view of anxiety to the TAM model. All the relationships in the model are supported, further confirming the need for universities and higher education institutes to pay attention to anxiety sources from both the external environment (e.g., fear of the disease, lack of social interaction) and the internal environment (e.g., computer anxiety, academic stress) in e-learning intention. As such, avoidance tends to make anxiety worse over time. Instead higher education institutes need to take small steps to reduce its negative impact. Specifically, the influential mechanism may provide more insights into the coping strategies. The PEOU is found significantly related to PU in both the anxiety group ($\beta = 0.652$) and the non-anxiety group ($\beta = 0.652$), and based on guidelines by Cohen (1992), both effect sizes are large. This implies that an enhanced PEOU would have a significantly positive effect on PU. As suggested by Nielsen (1994), the PEOU is closely related to the human-computer interaction. Thus, for technology developers, an enhancement in the PEOU (e.g. human-computer interface) contributes to an enhanced PU and in turn, further motivates more students' e-learning intention. Differently, the influential mechanism reveals that anxiety is prone to strengthen the PU-intention effects, implying that in an environment where students are potentially subjected to anxiety, improving the PU is one of the foremost effective ways to retain students in e-learning. Though this study does not provide empirical evidence on the direct effect of PU or intention on the anxiety relief, indeed, it is strongly recommended that the course instructors should redesign curricula with a more student-centered approach for online delivery to improve the PU, which could be a solution to care for students that are potential with anxiety issues and to keep them away from making the situation worse.

5.4 Theoretical Implications

The first contribution of this study revolves around incorporating a holistic view of anxiety to provide nuanced insights into students' e-learning intention in the COVID-19 pandemic. While computer anxiety is commonly considered an antecedent for e-learning intention, this study highlights the need to incorporate anxiety from other sources such as fear of the disease, academic stress, and lack of social interaction into the TAM model to provide a more enhanced view of students' e-learning intention. Further, based on the TAM model, this study reveals an influence mechanism of anxiety on e-learning intention. Since the TAM is widely applicable in other information system applications, it is expected that the influence mechanism can be extended to investigate the influence of anxiety on other information system acceptance. In this sense, this study also theoretically contributes to the knowledge on the technology acceptance of users subjected to environment anxiety.

6 Conclusion and limitations

The objective of this study is to examine (1) whether the anxiety level has a moderating effect on students' adoption of e-learning during the Covid-19; (2)if yes, how does the anxiety level moderate the relationship of the TAM constructs in terms of significant level and effect size. To address the two research questions, taking the opportunity of the massive adoption of e-learning during the first wave of the COVID-19 pandemic, we adopted the TAM model to examine the influence of anxiety on e-learning intention. Specifically, we recruit universities students from all over China that have the e-learning experience during the lockdown in the first wave of the COVID-19 pandemic. The respondents are classified into two groups according to the GAD-2 metric and the intergroup difference in the TAM constructs and the relationships are compared. Findings reveal that all perceptions in the TAM constructs are reduced in the anxiety group. Besides, compared to the non-anxiety group, all effects associated with PU are reinforced while those associated with PEOU are attenuated in the anxiety group. This study contributes to a better understanding of the influence of anxiety on e-learning intention, which further provides nuanced knowledge on the future adoption of e-learning for massive students in higher education. We advocate instructors and higher education institutions should take advantage of the significant PU-intention relationship by providing quality e-learning, which is paramount to coping with the anxiety among students. Apart from that, the technology developers need to appropriately improve the human-computer interface (PEOU) to enhance students' perception of performance benefit (PU) from the e-learning, which will, in turn, motivate their e-learning intention.

This study is not without limitations. First, this study provides a prototype attempt to investigate the influence of anxiety on e-learning where the different types of anxiety sources are synthesized. However, anxiety can stem from internal sources (computer anxiety, academic stress) and external sources (fear of the virus, lack of social interaction), which may have different influences on the e-learning intention. Therefore, future studies are encouraged to separately investigate the influence of the different types of anxiety to provide nuanced insights into their effect size. Second, though the GAD-2 is reported to have good sensitivity and specificity in measuring the generalized anxiety disorder (Kroenke, *et al.*, 2007), the reliability of the metric in the current study is not verified. This limitation is prone to be addressed in future work. Besides, we also considered using the GAD-7 scale because it provides much detail on the level of anxiety. Exploring the anxiety with a more detailed anxiety level may offer better insights into the influence of anxiety on e-learning. Finally, for simplicity, this study does not incorporate anxiety as an external variable to the TAM model as prior studies focused on computer anxiety did. Therefore, future studies are encouraged to introduce a different type of anxiety as external variables to the TAM model, which may offer value in revealing the influence mechanism of anxiety on e-learning.

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Appendix 1 Constructs and measurements

Constructs	Items	Measures	References
		Technological Acceptance Model (TAM)	
Perceived Usefulness (PU)	PU1	I believe E-learning improves my learning performance.	Wu and Zhang (2014); Kim, *et al.* (2010); Wu and Chen (2017)
	PU2	Using E-learning enhances my learning effectiveness.	
	PU3	Using E-learning easily translates the learning material into specific knowledge	
Perceive ease of use (PEOU)	PEOU1	Learning to use MOOCs is easy.	Chang (2010); Wu and Chen (2017);
	PEOU2	It is easy to become proficient in using MOOCs.	
	PEOU3	The interaction with MOOCs is clear and understandable	
Attitude toward using (ATT)	ATU1	I believe that using MOOCs is a good idea.	Chang (2010); Wu and Zhang (2014) Wu and Chen (2017);
	ATU2	I believe that using MOOCs is advisable	
	ATU3	I am satisfied with using MOOCs.	
Continuance intention (CI)	CIIU1	I intend to continue to use MOOCs in the future	Wu and Zhang (2014) Wu and Chen (2017);
	CI2	I will continue using MOOCs increasingly in the future.	
	CI3	My intentions are to continue using MOOCs in the future, at least as active as today	
Instrumental Support	DITS	Compared to my expectation, the ability of the current feature seems to clarify the knowledge that I need to learn	
		General Anxiety Disorders (GAD)	
Anxiety level	GAD1	Feeling Nervous, anxious, or on edge	Kroenke*, et al.* (2007)
	GAD2	Not being able to stop or control worrying	